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## THE EFFECTS OF FEEDBACK AND PREDICTABILITY ON HUMAN JUDGMENT

BETTY S. GOLDSBERRY
RICE UNIVERSITY

Technical Report #84-3
August, 1984







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# The Effects of Feedback and Predictability on Judgment

Betty S. Goldsberry

## Abstract

Previous research has found that when subjects are given cognitive feedback, they reach higher levels of achievement than when they are given outcome feedback. It was hypothesized that this finding was due in part to the predictability of the task environment since outcome feedback is at a distinct disadvantage as a sole means of conveying such information. A study was conducted to compare response and outcome feedback under three predictability conditions. The design included a control group receiving no feedback at all, two response groups differing in precision of feedback information, and two outcome feedback groups differing on a quantity dimension. Task predictability conditions averaged across five learning blocks were high ($r$ = .94), moderate ($r$ = .87) and low low ($r$ = .71). The study also attempted to clarify the definition of feedback and to equate the availability of task information in the various feedback conditions that were compared.

Contrary to expectations, the utility of outcome feedback was inferior to that of response feedback under all

three predictability conditions tested. In fact, an interaction revealed that the effect of increased predictability raised rather than lowered the disparity between outcome and response feedback performance. The results also revealed that a control group receiving no feedback at all performed as well as or better than those with feedback when the availability of task information was equated. Moreover, eliminating the memory requirement inherent in the use of outcome feedback only worsened performance. Similarly, adding precision to the response feedback condition beyond the level of mere directional error information did not improve performance.

The principal conclusions to be drawn from these findings are: (a) increasing predictability improves judgment performance but does not enhance the effectiveness of outcome feedback, (b) providing outcome feedback is actually detrimental to performance when the subject is adequately instructed regarding the underlying task structure, and (c) increasing the precision of response feedback beyond mere direction of error is of no apparent value in multiple-cue judgment tasks.

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# Introduction

It is now well established that human judgment capabilities are limited, and that decisions based largely on intuition can be seriously biased or flawed (Nisbett & Ross, 1980). Further, people are poor at recognizing the deficiencies in their own performance, and as a result, tend to be over confident (Einhorn & Hogarth, 1981; Slovic et al., 1977). Attempts to improve both performance and awareness through the use of systematic training procedures have met with only limited success (Slovic, 1982).

Naturally, a central feature in most such "debiasing" paradigms is a provision of feedback. Since knowledge of results (or feedback) has long been considered a sufficient--if not necessary--condition for learning (Holding, 1959), the question of why it is not more generally effective in moderating judgment and decision behavior has been of interest for some time (Fischhoff, 1975). Among the conclusions that have emerged are (a) the recognition that in many common judgment situations, feedback is insufficient, irrelevant, or even misleading (Einhorn, 1980) and (b) the observation that only certain types of feedback are useful when the relationships to be learned are probabilistic rather than deterministic (as is usually the case in judgment and decision tasks). More specifically, it has been suggested that the mere knowledge of the outcomes produced by a judgment or decision process (i.e. their accuracy, level of success, payoff, etc.) is relatively useless or even counterproductive, whereas information regarding the process itself (i.e. the task structure, the ideal response strategy, or both) can produce improvement (Deane et al., 1972; Hammond & Summers, 1965; Hoffman et al., 1981; Summers & Hammond, 1966).

Although considerable evidence has been gathered in support of the above generalizations, the issue of how to structure feedback for purposes of improving and/or sustaining judgment performance is far from resolved. For one thing, the outcome-process distinction is but one of many that have been applied to the feedback concept: feedback can be manipulated in a host of ways, all of which could have implications for judgment performance. For another, it has recently been pointed out that task characteristics in addition to the feedback itself--independently and in conjunction with feedback--can influence the efficacy of any particular kind of feedback. Adelman (1981), for example, has shown that task congruence, or the degree of correspondence between implied and actual properties of the task environment determine the relative effectiveness of outcome and process (or cognitive) feedback: outcome feedback is not only useful, but as effective as cognitve feedback when incorporated into a highly congruent task. At the risk of oversimplification, what this means is that a decision maker (DM) can benefit from outcome feedback if he/she has a good conception of the processes by which outcomes are produced; otherwise, such information only leads to confusion. Cognitive feedback, on the other hand, is useful for acquiring that understanding, but redundant once the basic structure is learned. Thus in a congruent task (where DM is already familiar with the basic processes), outcome feedback serves as well as cognitive feedback in maintaining performance.

The present study was designed to explore further the relative efficacy of outcome feedback in judgment as a function of task conditions. In this case, however, every effort was made at the outset to insure that DM was aware of the process or rule by which outcomes (criterion values) were related to the predictive information (cue values). Such conditions would be present in any real-world judgment task where cue-criterion relations were known. The task property of interest here was _task predictability_, or the extent to which the "process" relating cues to outcomes was reliable. The main issue was whether feedback type would interact with this task feature in a manner similar to that found by Adelman (1981) for congruence. That is, does the effectiveness of outcome (versus cognitive) feedback increase with task predictability as it does when the task becomes more congruent? In a sense, both manipulations could be viewed as ways of making the judgment task easier.

Although several investigations have speculated upon a predictability-feedback interaction (Adelman, 1981; Payne, 1982), none has yet demonstrated it.

Thus the principal hypothesis addressed in the present study was that outcome feedback should become more effective relative to cognitive feedback in shaping and sustaining judgment performance as task predictability increases. Since all subjects were familiar with the task structure (hence "congruence" was fixed at a high level), the cognitive feedback dealt primarily with the appropriate _response_ strategy. That is, DM presumably knew what the cue-criterion relationships were, and thus his/her only concern was how to produce responses in a manner consistent with this structure. The feedback indicated the degree of correspondence between the response strategy evidenced in DM's judgment behavior and the optimal strategy (therefore the cognitive feedback conditions are referred to as _response_ feedback in the remainder of this report).

The task, analytic approach, and interpretations involved in this study, like those of its predecessors, all draw heavily upon the so-called Brunswik Lens Model of judgment (Brunswik, 1952, 1955). Therefore, a brief review of this model is in order.

In essence, the "lens model" (illustrated in Figure 1) separates characteristics of the environment from characteristics of the human judge. The left portion of

Figure 1 represents the environment and illustrates the "true" relationship between the predictive cues and criteria, whereas the right portion represents the judge and illustrates cue-criterion judgment relationships. The left portion, therefore, permits a normative analysis of judgment while the right portion permits a descriptive analysis.

Tucker (1964) suggested that the relationship between the judgments and the criteria could be partitioned into several statistically independent components reflecting: (a) the judge's acquired knowledge of task properties, (b) his/her cognitive control in applying that knowledge, (c) the degree of predictability in the task environment, and (d) the nonlinearity in the judgments. The equation reads as follows:

$$R_a = G\, R_s R_e + C \sqrt{1 - R_s^2}\sqrt{1 - R_e^2} \qquad (1)$$

where

$R_a$ = the relationship (correlation) between the judgments and the criteria;

G = the correlation between the linear predictions of the judgments and the linear predictions of the criteria;

$R_s$ = the correlation between the judgments and the linear predictions of the judgments;

$R_e$ = the correlation between the criteria and the

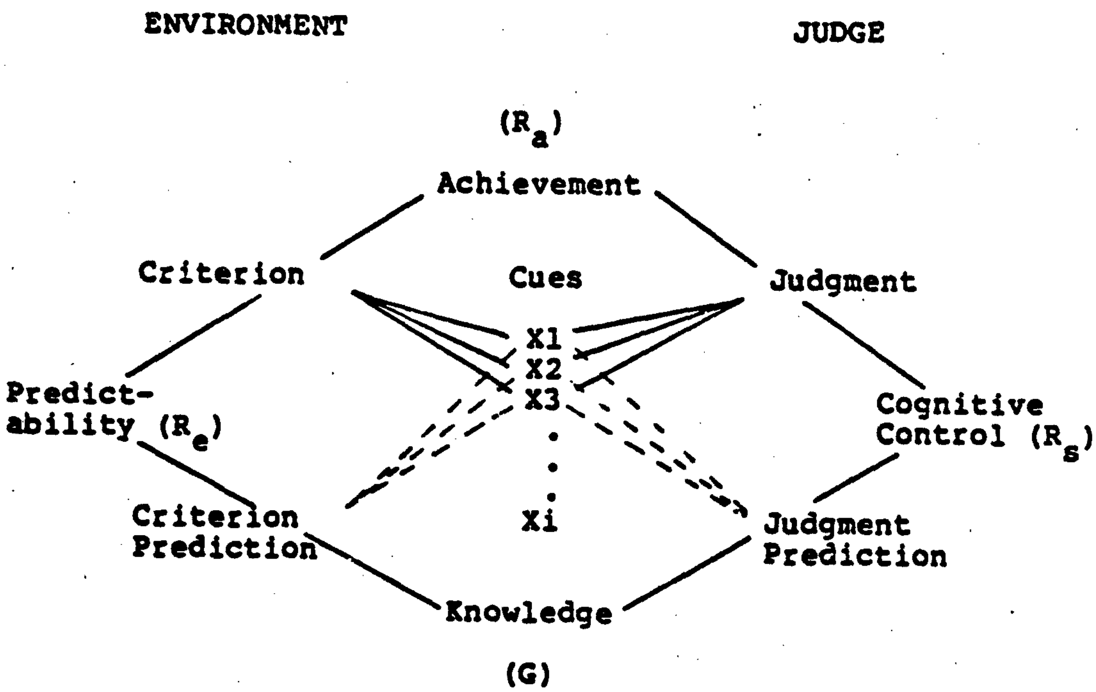



Figure 1: Brunswik's Lens Model

linear predictions of the criteria, a measure which places an upper limit on achievement;

C = the correlation between the variance in the task system and the variance in the response system, a measure which is an indication of nonlinearity in the judge's response strategy.

Hammond and Summers (1972) used the lens model to isolate two of these components--the acquisition of knowledge (G) and the application of knowledge ($R_s$). They defined acquisition as the extent to which the judge's cognitive system is isomorphic with (in the same form as) the task environment. They defined application, or cognitive control, as the extent to which acquired knowledge is utilized consistently in making judgments. The isolation of these two factors made possible an assessment of how feedback type and other task characteristics affect performance through use of multiple regression analysis.

In this application, regression is used to model the way in which information about the cues is used or should be used to produce a judgment. It accomplishes this by generating, from an intercorrelation matrix of cue dimensions, a linear regression equation that indicates how best to weight each cue dimension. If the cue values are regressed on the "correct" judgments (criteria), the linear model illustrates an optimal weighting strategy (a normative model of judgment); and if they are regressed on the "observed" judgments, the model illustrates a response weighting strategy (a descriptive model of judgment or the judge's "policy"). If, for example, the weight of a cue dimension was 1.0, it would indicate that the judge has relied completely on that dimension in making his judgments, whereas a zero weight would indicate that he has ignored the dimension completely.

The present research, then, used the lens model and multiple regression analysis to create a theoretical framework for the investigation of the effects of feedback type and task characteristics on human judgment. Since the requisite knowledge (i.e. proper cue-weighting strategy or G) was furnished directly through instructions, any effects of the manipulations were expected to appear in terms of the application of knowledge (i.e. cognitive control or $R_s$) and the overall achievement index (i.e. $R_a$).

# Method

## Subjects and Design

Seventy undergraduate psychology students participated in the research project as judges (subjects) in exchange for extra course credit or $12.00 in cash. Subjects were randomly assigned to five treatment groups defined on the basis of feedback type. They made judgments on three different hypothetical jobs, each representing a different level of predictability. The distinction between these five feedback groups and three jobs is explained in greater detail in the next section.

To control for possible order effects, presentation of the three jobs was counterbalanced; to minimize fatigue effects, each job was presented at a different session. Each session was divided into a warm-up period and five practice blocks. The experimental design, therefore, was a mixed model 5 (feedback type) by 3 (task predictability) by 5 (practice block) factorial with 14 subjects per group.

## Task

The judgment task was chosen on the basis of its common usage in human judgment research and the likelihood that it would be meaningful for a wide variety of potential subjects. It consisted of evaluating the overall suitability of hypothetical job applicants based upon their ratings on three skill dimensions (i.e. the cue values). Using the weighting strategy shown in Table 1, subject were required to integrate the three cue values for each of 320 applicants into a single suitability rating on a scale of 1 (least suitable) to 9 (most suitable). Since this weighting

TABLE 1

Optimal Weighting Strategy

| | Skill Rating | | |
|---|---|---|---|
| | 1 | 2 | 3 |
| Regression Weight | .50 | .30 | .20 |

strategy was, by definition, the normatively optimal model of the task environment (left portion of the lens model), it was used to generate the criteria and the criterion predictions characterizing the task. Random error was then added to the criteria to produce the three levels of predictability (one for each job): (a) high, in which $r = .94$, (b) moderate, in which $r = .87$, and (c) low, in which $r = .71$. Therefore, three different sets of criteria were generated and only one set of predictions. In the low predictability condition, 50 percent of the variance was due to random error; in the moderate and high predictability conditions, the corresponding error variances were 24 and 12 percent, respectively. These three sets of criteria were used as the basis for generating feedback in all four of the feedback groups.

Each applicant profile (illustrated in Figure 2) contained three skill ratings and a set of irrelevant biographical information. It was presented via a Visual 200 terminal controlled by an Advanced Systems/9000 computer. The skill ratings were generated orthogonally from a normal distribution of numbers ranging from 1 to 9 with a mean of 5 and a variance of 2. Biographical data were randomly selected from the Houston, Texas telephone directory.

The five types of feedback were: (a) no feedback (control), (b) non-historical outcome feedback, (c) historical outcome feedback, (d) comparative response feedback, and (e) exact response feedback. In the control condition (a), the subject was forced to rely entirely upon the strategic information provided by the instructions (see Table 1): there was no opportunity for judgment-to-judgment calibration as in the four feedback conditions. The two outcome feedback conditions (b and c) afforded the subject knowledge of the "correct" response as generated by the environmental model (including the random error component). They differed in that non-historical feedback (b) indicated

| | |
|---|---|
| Name: | Mary Frances Smith<br>522 Pontiac Avenue<br>Houston, Texas 77024 |
| Telephone No. | 567-3443 |

| Rating Skill No. | Rating |
|---|---|
| 1 | 7 |
| 2 | 2 |
| 3 | 5 |

Your response is _______.

Figure 2: Profile format.

the correct response for the current applicant only, whereas historical feedback (c) displayed the results for the past 20 applicants as shown in Figure 3. This manipulation was designed to control for the role of memory in any obtained outcome-cognitive feedback difference. That is, if the typical inferiority of outcome feedback is due to the subject's inability to remember how previous responses turned out, as some have suggested, then historical outcome feedback should ameliorate the deficiency.

Finally, the two cognitive (response) feedback conditions (d and e) provided the subject with information on how his cue-weighting policy over the last 20 judgments (right-hand side of the lens model) compared to optimal (left-hand side of the lens model). It was obtained by regressing the actual judgments onto the cue values (ratings) and displaying the resulting beta weights either numerically in comparison to the optimal ones (e above as illustrated in Figure 4), or in comparative terms (d above as illustrated in Figure 5). In the latter case, the "tolerance interval" for a correct response ("OK" feedback) was a captured weight set to within ±.05 units of the optimal weight for a particular cue.

## Procedure

All subjects participated in three sessions, each approximately 60 minutes in length and scheduled one week

| First Skill | Second Skill | Third Skill | Your Response | Correct Response |
|---|---|---|---|---|
| 5 | 2 | 7 | 4 | 4 |
| 3 | 1 | 8 | 7 | 3 |
| 7 | 3 | 2 | 5 | 5 |
| . | . | . | . | . |
| . | . | . | . | . |
| . | . | . | . | . |
| 1 | 6 | 4 | 4 | 3 |

Figure 3: Historical outcome feedback display.

| Rating Skill | Optimal Weighting | Your Weighting |
|---|---|---|
| 1 | .50 | .67 |
| 2 | .30 | .27 |
| 3 | .20 | .06 |

Figure 4: Exact response feedback display.

| Rating Skill | Optimal Weighting | Your Weighting |
|---|---|---|
| 1 | .50 | Too high |
| 2 | .30 | OK |
| 3 | .20 | Too Low |

Figure 5: Comparative response feedback display.

apart. At the beginning of each session, written instructions were given describing the job, the assessment procedure, the feedback type, and the optimal weighting strategy. To insure full understanding of this information, instructions were augmented by a graphical illustration of how each skill dimension correlated with on-the-job performance. The subjects were also taught how to use the Visual 200 terminal to enter their judgments.

Subjects were told that each session would be devoted to making suitability ratings on applicants for three different jobs. The normality and dependence features of the profiles were also explained so the subjects would not be misled searching for nonexistent profile structures. The actual job titles and skill dimensions, however, were not identified so that subjects would not be influenced by prior knowledge or familiarity with the jobs.

All subjects were paced through 20 warm-up profiles followed by 300 experimental ones with the aid of a tape recording of "beeps" presented at 10-second intervals. Between each set of 20 profiles (a unit) there was a 60-second pause during which the control and non-historical groups rested and the other three groups received their end-of-unit feedback.

## Measures

The scaled judgments served as the basis for two sets of derived measures: two product measures (hit-rate and achievement) and two process measures (knowledge and cognitive control). The product measures indicated how closely judgment performance approximated the defined optimal while the process measures examined the inferred cognitive elements underlying that performance.

The model adopted for this purpose was the standard linear regression approach commonly used in human judgment research and explained in the Introduction. The optimal weights assigned to the various skill dimensions are shown in Table 1. _Hit-rate_ was simply the proportion of a subject's judgments that matche the output of the "true" or ecologically valid weighting model. _Achievement_ was the correlation between the subject's judgments and the optimal model's "judgments." _Knowledge_, or the subject's understanding of the optimal weighting strategy, was indexed by the correlation between the criteria produced by the optimal weighting strategy and judgments produced by a model of the subject's weighting strategy. The latter, of course, was derived from the subject's actual judgments through the use of multiple regression analysis to "capture" his policy. _Control_ was indexed by the correlation between judgments predicted on the basis of the subject's captured policy and ones he or she actually produced.

The mathematical relationship between achievement and the process measures (knowledge and control) was discussed in the Introduction. For present purposes, this relationship, which is a mathematical statement of the lens model as set forth in equation 1, is simplified as follows:

$$R_a = G\ R_s\ R_e \qquad (2)$$

because specification of an optimal weighting strategy makes the criterion as predictable as $R_e$, and the optimal strategy is linear (eliminating the need for the right-most term in equation 1). The simplified equation renders the distinction among measures used in the present research apparent. The $R_a$ term represents achievement which can be partitioned into knowledge (G), control ($R_s$), and predictability ($R_e$). Judgments are, therefore, accurate ($R_a$) to the extent that they correspond with the actual suitability of the applicants as reflected by the substantive properties of the task. It follows, therefore, that a subject can be accurate in his judgments to the extent that he has a predictable task structure ($R_e$), he understands the structure (G), and he is capable of using that understanding consistently ($R_s$).

## Analysis

Product and process measures were determined in keeping with the definitions just presented. Since task predictability is a component of performance as well as an independent variable in this research, absolute and relative measures of performance were calculated and analyzed. The absolute performance measures were the observed block scores while the relative performance measures were calculated by dividing each observed block score by the optimal block score (obtained by applying the optimal weighting strategy to the cue values). Naturally, the optimal block score declined as predictability was reduced. It also varied somewhat across learning blocks since predictability was not counterbalanced over blocks in this study. Tables 2 and 3 show the optimal block scores used to calculate the relative achievement and hit-rate measures, respectively.

Separate analysis of variance procedures were performed on <u>absolute</u> and <u>relative</u> measures in order to assess the significance of main effects and interactions among the independent variables. Dunnett tests, which compare treatment means to a control group, were also used to compare the effects of each feedback type with the no feedback control. In addition, Newman-Keuls tests of paired comparisons were carried out, when appropriate, to isolate the pattern of significant effects. These tests were performed in a manner described by Winer (1962).

Table 2

Optimal Achievement Scores

Total Job Task Predictability (r)

| | High | Moderate | Low | Mean |
|---|---|---|---|---|
| Blocks | | | | |
| 1 | .83 | .87 | .72 | .81 |
| 2 | .95 | .91 | .80 | .87 |
| 3 | .97 | .87 | .61 | .82 |
| 4 | .98 | .92 | .78 | .90 |
| 5 | .96 | .86 | .64 | .82 |
| Mean | .94 | .87 | .71 | .84 |

Table 3

Optimal Hit-rate Scores

Task Predictability Levels (% correct)

| | High | Moderate | Low | Mean |
|---|---|---|---|---|
| Blocks | | | | |
| 1 | 100 | 63 | 32 | 65 |
| 2 | 100 | 62 | 40 | 67 |
| 3 | 100 | 50 | 32 | 60 |
| 4 | 100 | 63 | 45 | 78 |
| 5 | 100 | 65 | 50 | 72 |
| Mean | 100 | 60 | 40 | 67 |

# Results and Discussion

For purposes of clarity in exposition, the principal findings are organized around four major questions addressed by this research: (a) Does task predictability influence performance? (b) Does feedback type influence performance? (c) Does practice influence performance? and (d) Does feedback efficacy differ as a function of task predictability? The data bearing on each of these questions will be preceded by a brief discussion of the expected results and their relevance to human judgment. Findings will be based on analyses of variance performed on the absolute hit-rate ($H_a$), relative hit-rate ($H_r$), absolute achievement ($R_a$), relative achievement ($R_r$), knowledge ($G$), and control ($R_s$) measures of performance which were described in detail earlier.

Feedback types will be represented by the following abbreviations: (a) T, for the control group which was given only task information, (b) N, for the non-historical outcome group, (c) H, for the historical outcome group, (d) C, for the comparative response group, and (e) E, for the exact response group.

1. Does task predictability influence performance?

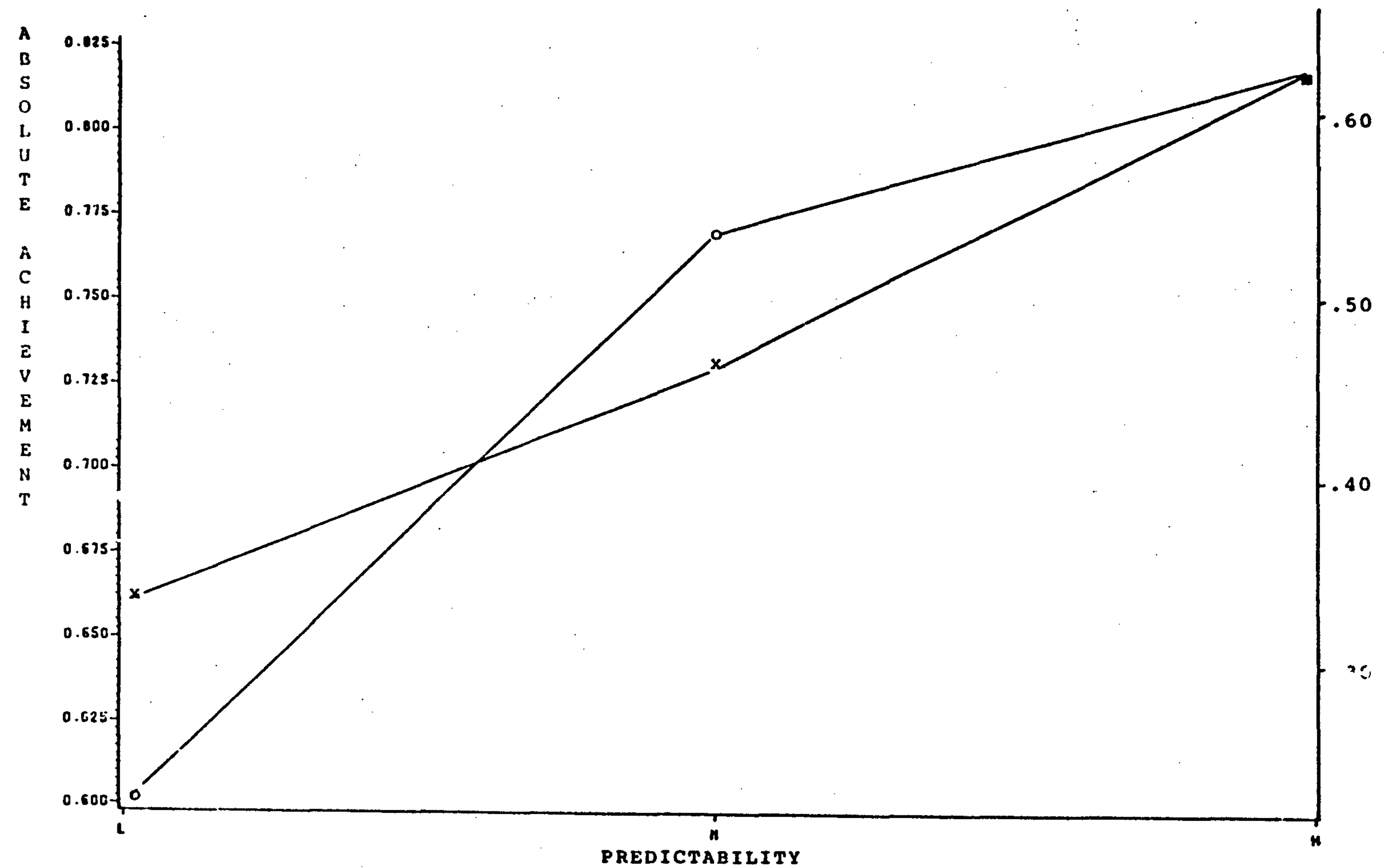
Task predictability can have two different types of influence on performance. First, as an independent variable and means of manipulating a substantive property of the judgment task, predictability can alter the performance of the optimal weighting strategy. A reduction in predictability, therefore, should produce a performance decrement even if the subject makes accurate and consistent usage of the available task information. Second, predictability can have an effect on the way in which subjects process the information presented to them. This, of course, is the more interesting influence from a psychological standpoint. By contrast, the first influence is important in that it serves as an indication of the subject's sensitivity to the manipulation--in essence a method check.

As noted in the Method section, two different kinds of performance measures (absolute and relative) were used to explore the effects of predictability on judgment. The influence of predictability as a manipulator of the task content was investigated by analyzing the absolute hit-rate and achievement measures. A significant effect for these measures would suggest that subjects were trying to use the optimal weighting strategy to make their judgments or at least that they were sensitive to the manipulation. The influence of task predictability as a cognitive component of performance was investigated by analyzing the relative performance measures since they reflect performance after manipulation effects have been removed. Significant effects for both absolute and relative measures were anticipated.

In general, the predictability manipulation had the desired effect on performance, for as predictability increased, so did performance. Although this finding comes as no surprise, it is nonetheless important because it suggests that subjects were sensitive to this task property and were trying to maximize their performance. As illustrated in Figure 6, both absolute product measures of performance yielded significant effects for task predictability, $F\ (2, 130) = 672.15$, $p < .01$ for achievement, and $F\ (2, 130) = 377.70$, $p < .01$ for hit-rate.

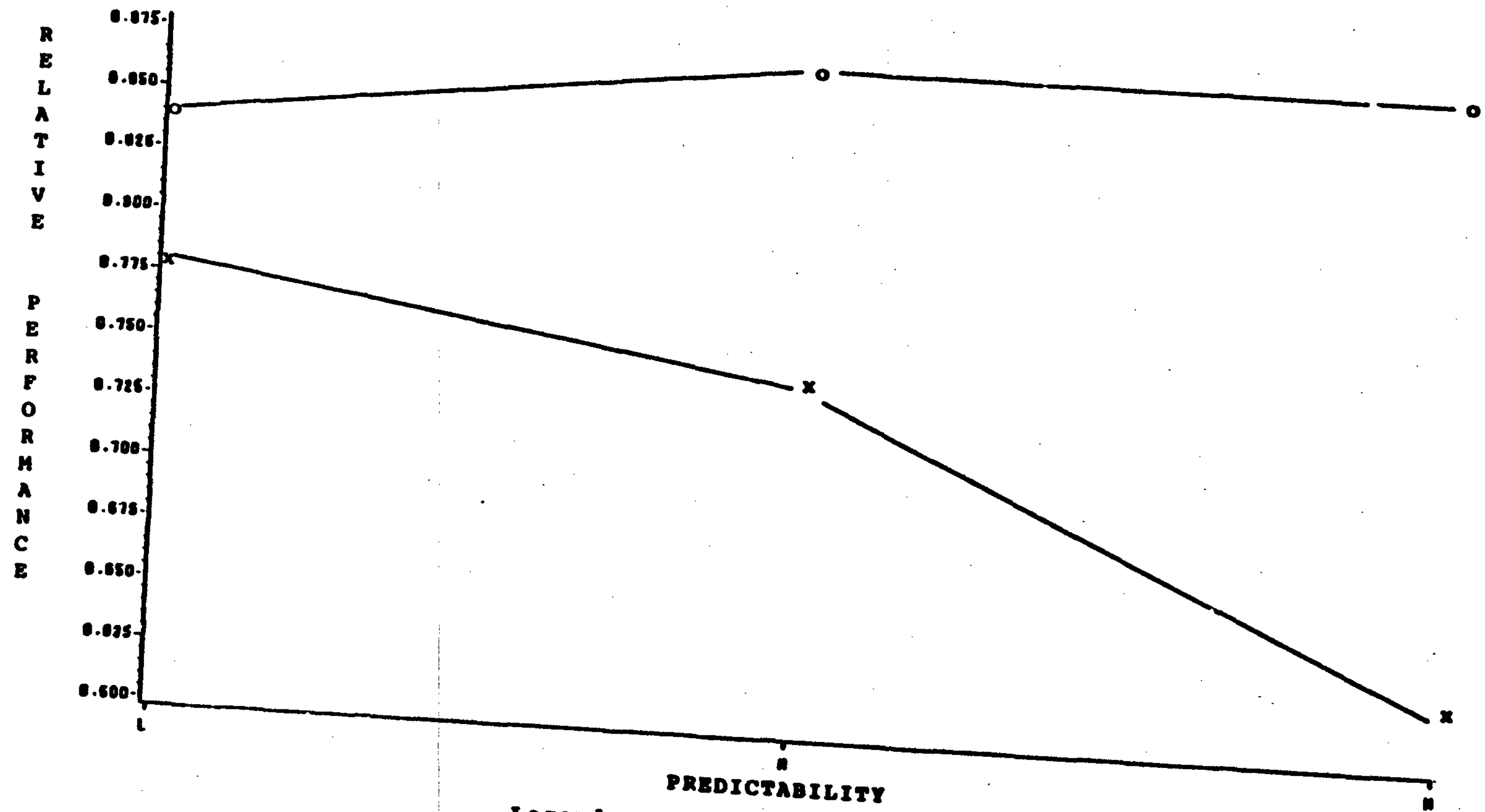
Predictability was also found to have a significant effect on relative performance. The two relative indices did not agree, however, on the nature of this effect. Figure 7 indicates that relative achievement increased with an increase in predictability, $F\ (2, 130) = 8.01$, $p < .01$, and that relative hit-rate decreased with an increase in predictability, $F\ (2, 130) = 45.63$, $p < .01$.

The ambiguity suggested by the relative measures could be an artifact of the way accuracy was defined for hit-rate: only an exact match between the subject's judgment and the value produced by the optimal weighting model was considered a "hit." Consider the optimal hit-rate values shown in Table 3. Under high




Legend: Cond o–o–o A x–x–x H

FIGURE 6: ABSOLUTE PERFORMANCE BY PREDICTABITY.




Legend: Cond o–o–o A x–x–x H

FIGURE 7: RELATIVE PERFORMANCE BY PREDICTABILITY.

predictability, the model was 100 percent correct by definition. Since even a well-calibrated subject would have trouble approximating this level, given that a judgment had to be perfect to be considered correct, one would expect relative hit-rate to be rather low. Under low predictability, on the other hand, the model was correct only about 40 percent of the time, a considerably easier standard against which to express the subject's performance. Even random responding would have yielded a relative hit-rate of nearly 25 percent under this condition (compared to about 11 percent under high predictability). Had a more lenient criterion been set for the definition of a "hit," such as a one-unit confidence interval around the model's judgments, relative hit-rate might have produced a trend more similar to that of relative achievement.

The process measures, knowledge and control, provide insight into the manner by which cognitive aspects of judgment affect performance. As illustrated in Table 4, they reveal that when predictability is increased from the low to the moderate level, both the understanding and the application of task structure information increases; but when it is increased further to the high predictability level, no additional improvement in cognitive processing occurs. Although small in absolute terms, the difference between low and moderate predictability yielded a significant effect of task predictability for both

TABLE 4

Mean Process Measures under

Three Predictability Conditions

| | Measures ($\underline{r}$) | |
|---|---|---|
| | Knowledge | Control |
| Predictability Level | | |
| Low | .88 | .86 |
| Moderate | .89 | .87 |
| High | .89 | .87 |
| Mean | .89 | .87 |

knowledge, $F$ (2, 130) = 4.92, $p < .01$, and control, $F$ (2, 130) = 3.70, $p < .03$. Hence, an increase in task predictability can significantly improve these two aspects of cognition; but if they are already at a limit dictated perhaps by mental capability or capacity, no further improvement will occur.

Task predictability, therefore, had a significant, though very small, effect on judgmental knowledge and control. As predictability increased, so did these aspects of judgment, although perhaps limited by a "ceiling" associated with the particular properties of the task.

2. Does feedback type affect performance?

The present study was designed to control for the typical confounding of task knowledge and feedback type. In previous studies, only subjects receiving cognitive feedback had access to specific (and important) knowledge of the formal task structure. By providing such information to all feedback groups via instructions, the present design permitted a fair comparison of response and outcome feedback conditions. The comparison of each feedback type with a control group receiving no feedback (task information only), therefore, isolated its utility in judgment. In light of recent findings, all feedback types tested were expected to provide some benefit, at least under some conditions, with response feedback generally being more beneficial than outcome feedback.

The results revealed that the type of feedback presented had a significant overall effect on performance for both absolute indices, $F\ (4,\ 65) = 7.82$, $p < .01$ for achievement and $F\ (4,\ 65) = 4.21$, $p < .01$ for hit-rate. However, contrary to expectations, Table 5 illustrates that the two response feedback groups performed at about the same level as the control group, but all three were better than the two outcome feedback groups. This relationship was supported by the results of Dunnett tests which revealed that for absolute measures, performance under exact and comparative conditions (response feedback) was not significantly different from the control ($p > .05$); but historical and non-historical conditions (outcome feedback) were significantly inferior to the control ($p < .05$). The results of Dunnett tests also revealed that for relative indices, only historical group performance was significantly inferior to the control ($p < .05$). These findings generally challenge the utility of all four types of feedback tested when subjects are informed of the proper weighting strategy prior to their judgments. It does, however, corroborate the evidence that outcome feedback is detrimental to judgment performance.

It is apparent from the relative performance measures that when the effect of predictability as an aspect of task content is removed, the relationships between feedback

Table 5

Mean Product Measures under

Five Feedback Conditions

| | Measures | | | |
|---|---|---|---|---|
| | Absolute | | Relative (ratios) | |
| | $H_a$ (%) | $R_a$ ($r$) | $H_r$ | $R_r$ |
| Feedback Types | | | | |
| No feedback | | | | |
| Control | 50 | .76 | .77 | .90 |
| Outcome feedback | | | | |
| Non-historical | 43 | .71 | .69 | .84 |
| Historical | 40 | .67 | .66 | .79 |
| Response feedback | | | | |
| Comparative | 47 | .75 | .69 | .88 |
| Exact | 50 | .75 | .75 | .88 |
| Mean | 47 | .73 | .71 | .86 |

types is unchanged. Significant feedback type effects appeared for both relative achievement, $F(4, 65) = 7.51$, $p < .01$), and relative hit-rate measures, $F(4, 65) = 2.86$, $p < .03$.

A comparison of the two types of outcome feedback suggests that preserving historical outcome data (cues, judgments, and criteria for the past 20 profiles) hurts rather than helps the decision maker. This finding was supported by a Newman-Keuls test that revealed a significant difference in absolute achievement between the two outcome feedback groups ($p < .05$). Relative achievement was also lower when a history was available, but the difference was not significant. It will be recalled that this manipulation was introduced in order to determine whether deficiencies of memory could explain the previously reported inferiority of outcome feedback. If the decline was due to failure of memory, performance should have been better with the historical record. Since the trend was in the opposite direction, failure of memory would not seem a reasonable explanation.

The detrimental effect of historical outcome feedback can, however, be explained with reference to the process measures. Inspection of the knowledge and control measures in Table 6 reveals that the subjects receiving a history of their judgments exhibited less control over their response strategies than did those without such a history. A

Table 6

Mean Process Measures under
Five Feedback Conditions

| | Measures (r) | |
| --- | --- | --- |
| | Knowledge | Control |
| Feedback Type | | |
| No feedback | | |
| Control | .90 | .92 |
| Outcome feedback | | |
| Non-historical | .87 | .86 |
| Historical | .87 | .80 |
| Response feedback | | |
| Comparative | .89 | .88 |
| Exact | .90 | .89 |
| Mean | .89 | .87 |

Newman-Keuls test supported this conclusion, the mean difference of .06 between these two outcome feedback conditions being highly significant ($p < .01$) for the control index. By contrast, the results for the knowledge index were identical whether or not history was displayed. Thus the decline in performance is clearly attributable to the effect that historical information has on the subject's ability to apply his or her own policy consistently.

Turning to the more constructive feedback types, it appears that feedback with the precision of regression weights leads to no better performance than comparative information based on those regression weights. This is supported by the fact that a Newman-Keuls test yielded no significant difference ($p > .05$) for the two response groups on any of the measures analyzed. Regression weights, therefore, are probably simplified to some extent during cognitive processing. This research does not permit speculation on the degree of simplification that takes place but it does suggest that regression weights are no more useful than comparative information derived from them, at least under the conditions studied here.

In summary, feedback was found not to have the expected positive effect on performance. Response feedback yielded performance similar to no feedback at all, while outcome feedback yielded considerably poorer performance. A principal consequence of outcome feedback was its detrimental effect on cognitive control, a detriment which was exacerbated by the addition of historical information (i.e. prior outcome data).

3. Does practice influence performance?

Learning a cognitive skill such as the one used in this research has been conceptualized as a three stage mental process (Fitts, 1964). The first stage involves an initial encoding of the skill into a form sufficient to generate the desired behavior to some crude extent (i.e. rule learning). This stage is characterized by rapid learning and sometimes verbal mediation or rehearsal while the task is being attempted. The second or "associative" stage involves the "smoothing out" or perfecting of the skill performance. This stage is characterized by a slowing down of learning while gradually detecting and eliminating errors in the initial understanding of the skill. Concomitantly, there is a dropout of verbal rehearsal. The third or "autonomous" stage involves even slower but continued improvement in performance over a long period of time.

When the subjects in this experiment were presented with an optimal weighting strategy and given an opportunity to practice using it prior to the experimental trials, the intent was to focus on the latter of these stages--eliminating for the most part the early rule-learning stage which has been the emphasis in most probability-learning research. Therefore, results were expected to reveal a gradual but consistent improvement in performance across blocks, or at the very least sustained application of the rules learned at the outset. The justification for this orientation was the practical consideration that in most real-world decision systems, DM would be appraised of any known cue-criterion relations.

No attempt was made to counterbalance predictability over blocks and, as a result, there was a degree of confounding between these variables, as illustrated in Table 2 (maximum achievement possible). However, average predictability was approximately equal for the three most widely spaced blocks ($r$ = .81, .82, and .82 for blocks 1, 3, and 5, respectively). Consequently, analysis of practice effects was limited to these three blocks in order to control predictability.

Looking first at the achievement index (Figure 8), the results show the anticipated gradual improvement in only three of the five feedback groups: control, non-historical outcome, and comparative response conditions. The historical outcome and exact response groups showed an increase on block 3 and a decrease on block 5, an effect which may have been due to the increased mental load or stress imposed by these feedback conditions. In any case, analysis revealed a significant effect of practice on absolute achievement,

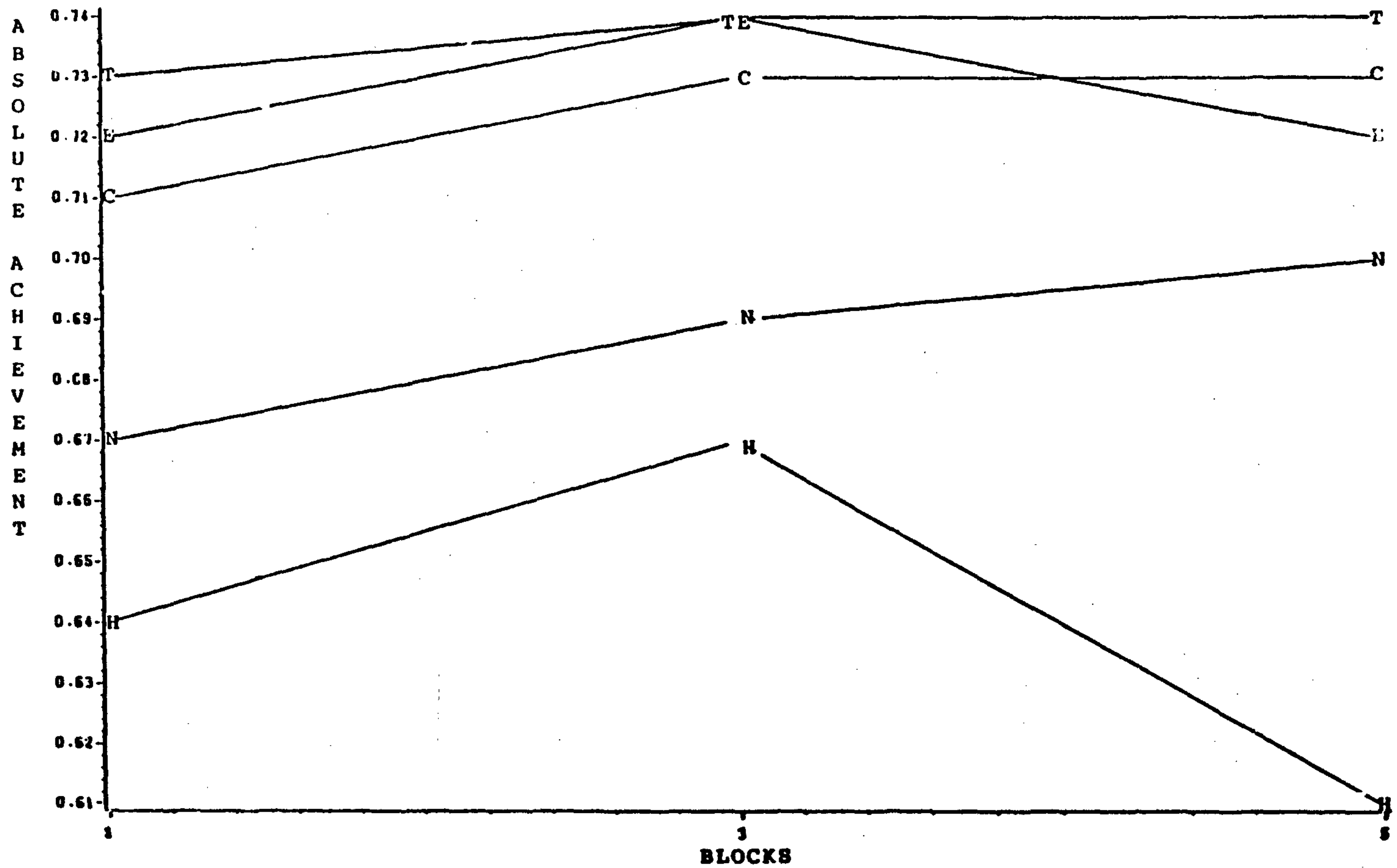



FIGURE 8: ABSOLUTE ACHIEVEMENT BY BLOCKS.

$F$ (2, 130) = 5.89, $p < .01$, but mean performance collapsed across the five groups did not suggest a typical learning function (.69, .71, and .70 respectively for the three blocks). Rather, the above-mentioned distinction between feedback type functions was supported by a significant type by block interaction, $F$ (8, 130) = 2.19, $p < .03$. The trends for hit-rate (Figure 9) were similar in form to those for achievement, but the feedback type by blocks interaction did not reach significance, $F$ (8,130) = 1.15, $p < .34$.

Turning to the component process measures (knowledge and control), improvements occurred only in blocks 1 and 3, and none of the interactions with feedback approached significance. Figure 10 shows that knowledge averaged across groups increased from G = .79 in block 1 to G = .92 in block 3 but declined slightly in block 5 (G = .90), $F$ (2, 130) = 507.32, $p < .01$; Figure 11 shows a less dramatic but still significant trend for control, $F$ (2, 130) = 4.95, $p < .01$. The sharp increase in knowledge between blocks 1 and 3 suggests that perhaps the rule-learning stage was not completed in the warm-up period as planned and that subjects were still encoding task structure information to some extent during the early blocks.

Taken together, these results suggest that practice has a significant effect on performance but the nature of the effect is specific to both the feedback type and the

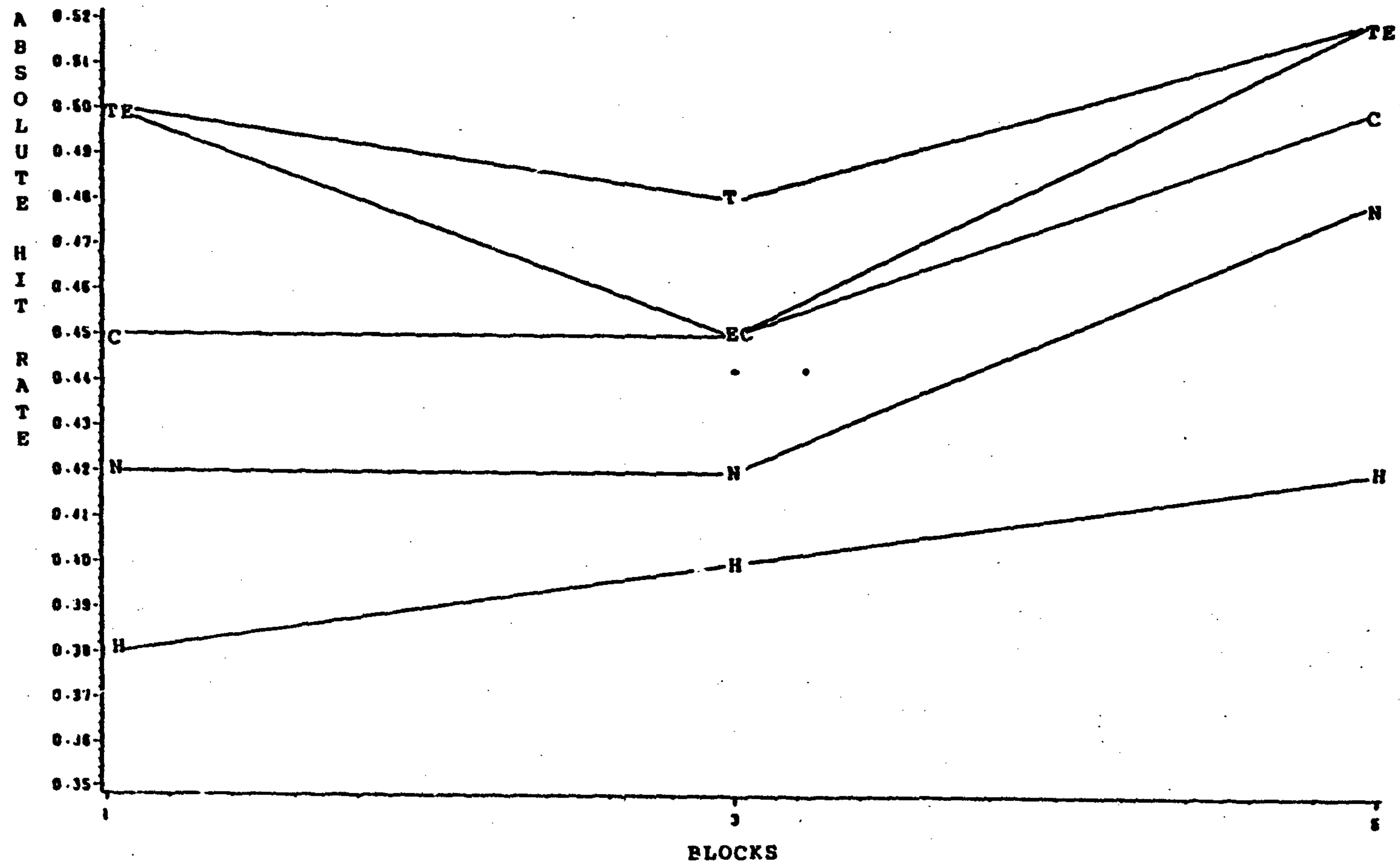



FIGURE 9: ABSOLUTE HIT RATE BY BLOCKS.

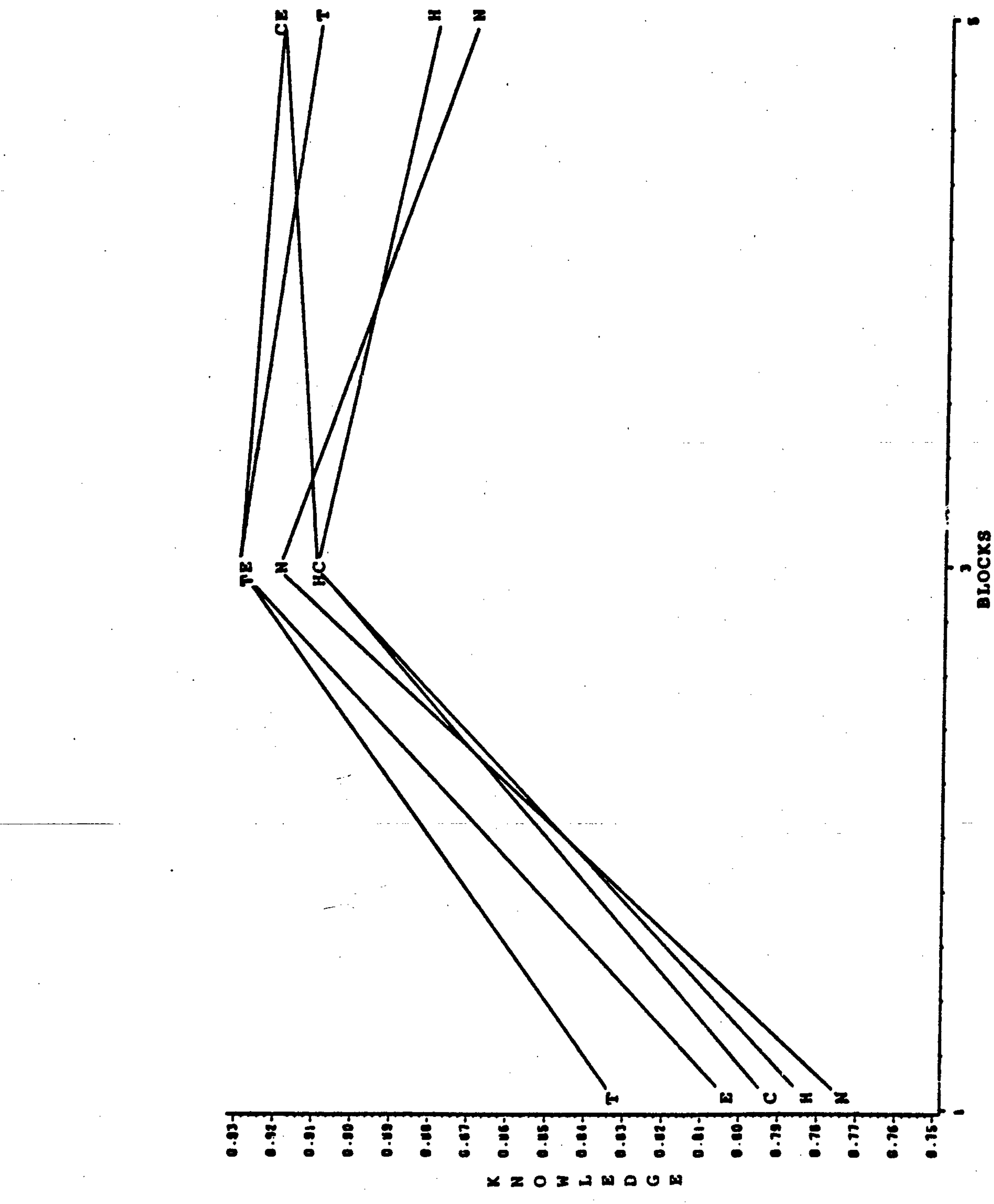



FIGURE 10: KNOWLEDGE E’ BLOCKS.

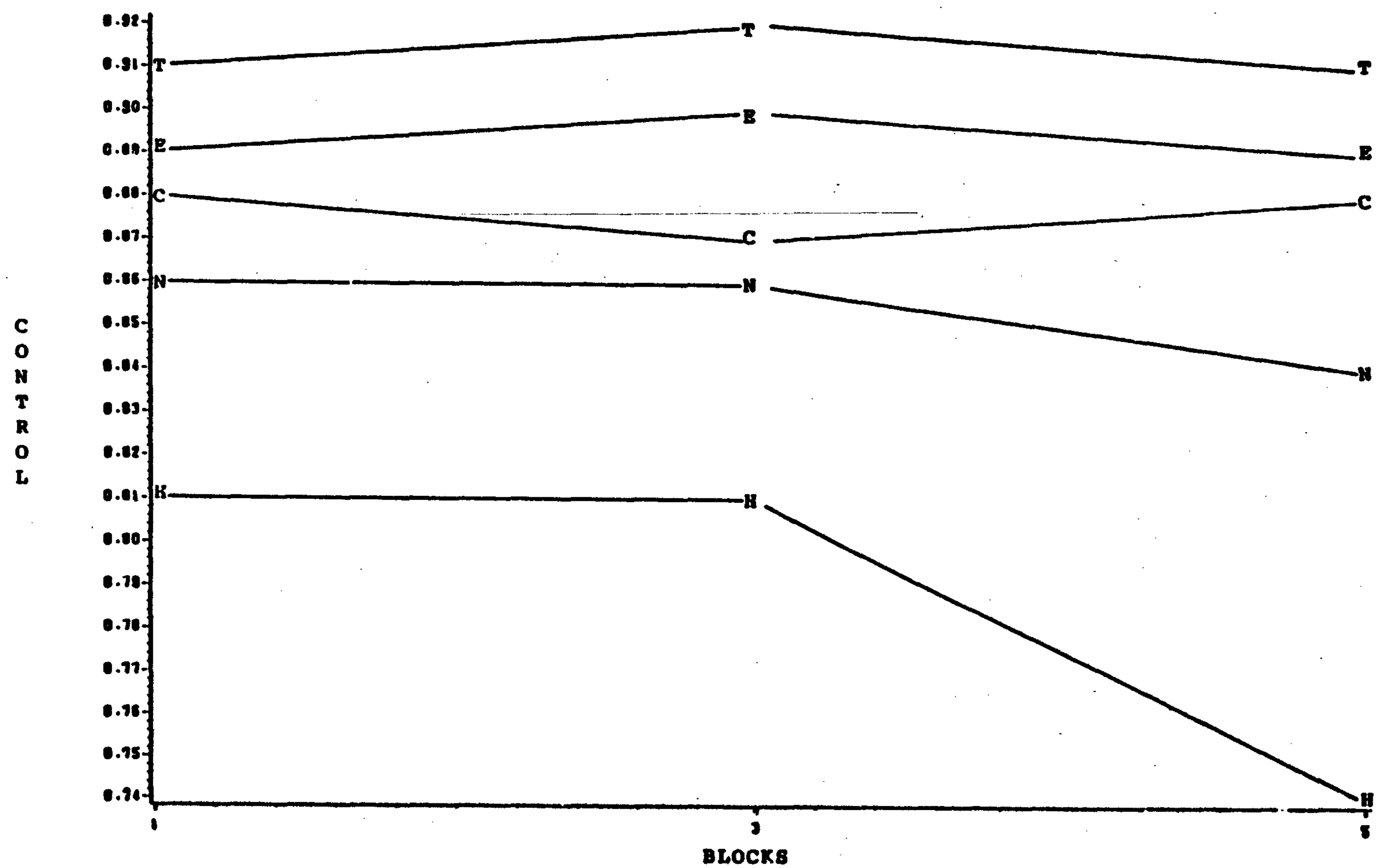



FIGURE 11: CONTROL BY BLOCKS.

measure used to evaluate it. In addition, early practice influences performance by improving the subject's understanding of task structure (knowledge) more so than his or her application of that knowledge (control).

4. Does feedback efficacy differ as a function of predictability?

It was hypothesized that the difference between the effects of outcome and response feedback would diminish as predictability was increased. Response feedback was expected to yield high performance at all three levels of predictability tested, while outcome feedback was expected to do so only when predictability was high. Therefore, the difference between outcome and response feedback performance was expected to decline as predictability increased, resulting in a feedback type by predictability interaction.

Findings did not support this hypothesis even though a feedback type by predictability interaction was obtained in the absolute hit-rate measure, $F$ (8, 130) = 4.40, $p < .01$. As illustrated on Figure 12, the direction of this interaction effect was exactly opposite that predicted (i.e. the differences among feedback conditions increased with predictability). A similar trend occurred for the absolute achievement measure (Figure 13), but the effect was not significant, $F$ (8, 130) = 1.57, $p < .14$.

The relative measures produced somewhat less consistent

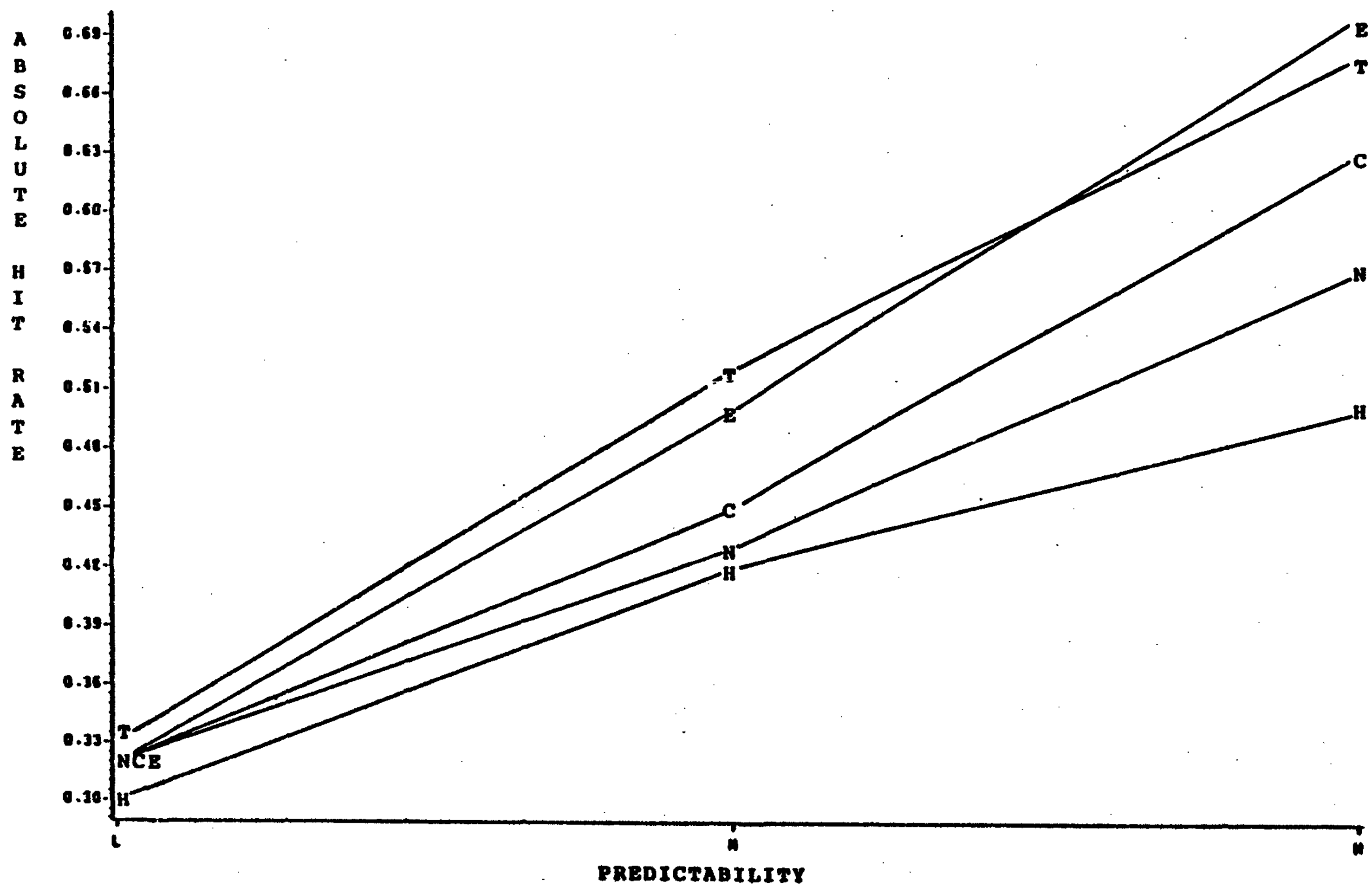



FIGURE 12: ABSOLUTE HIT RATE BY PREDICTABILITY.

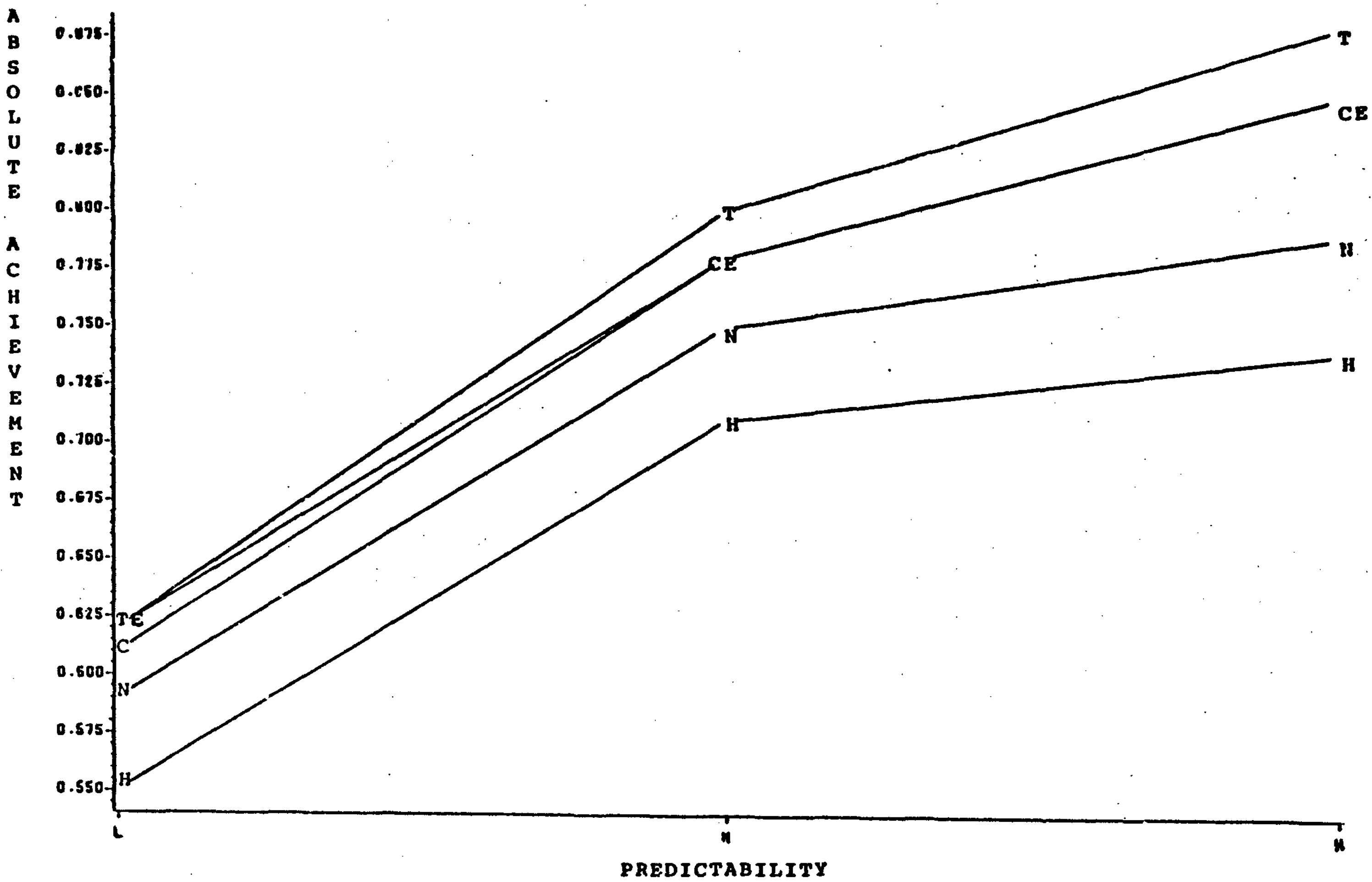



FIGURE 13: ABSOLUTE ACHIEVEMENT BY BLOCKS.

findings than did the absolute measures. Relative hit-rate (illustrated in Figure 14) showed a sharp, negative relation between predictability and performance, whereas achievement (Figure 15) showed a gradual, positive one. Whatever their shape and direction, however, the effects of feedback conditions on these functions were consistent with the absolute measures. Performance was degraded by outcome feedback and the expected interaction did not materialize. Only that for relative hit-rate was significant, $F$ (8, 130) = 2.42, ($p < .02$). Apparently, the decline in relative achievement for the outcome feedback conditions (Figure 15) was not large enough to cause a feedback by predictability interaction, $F$ (8, 130) = .58, $p < .79$.

Taken together, these results suggest that unlike task congruence, task predictability does not increase the comparability of cognitive (response) and outcome feedback effects. Rather, it would appear that outcome feedback becomes <u>more</u> detrimental to judgment performance as predictability increases, and is generally inferior to no feedback at all, regardless of whether performance is measured in absolute or relative terms.

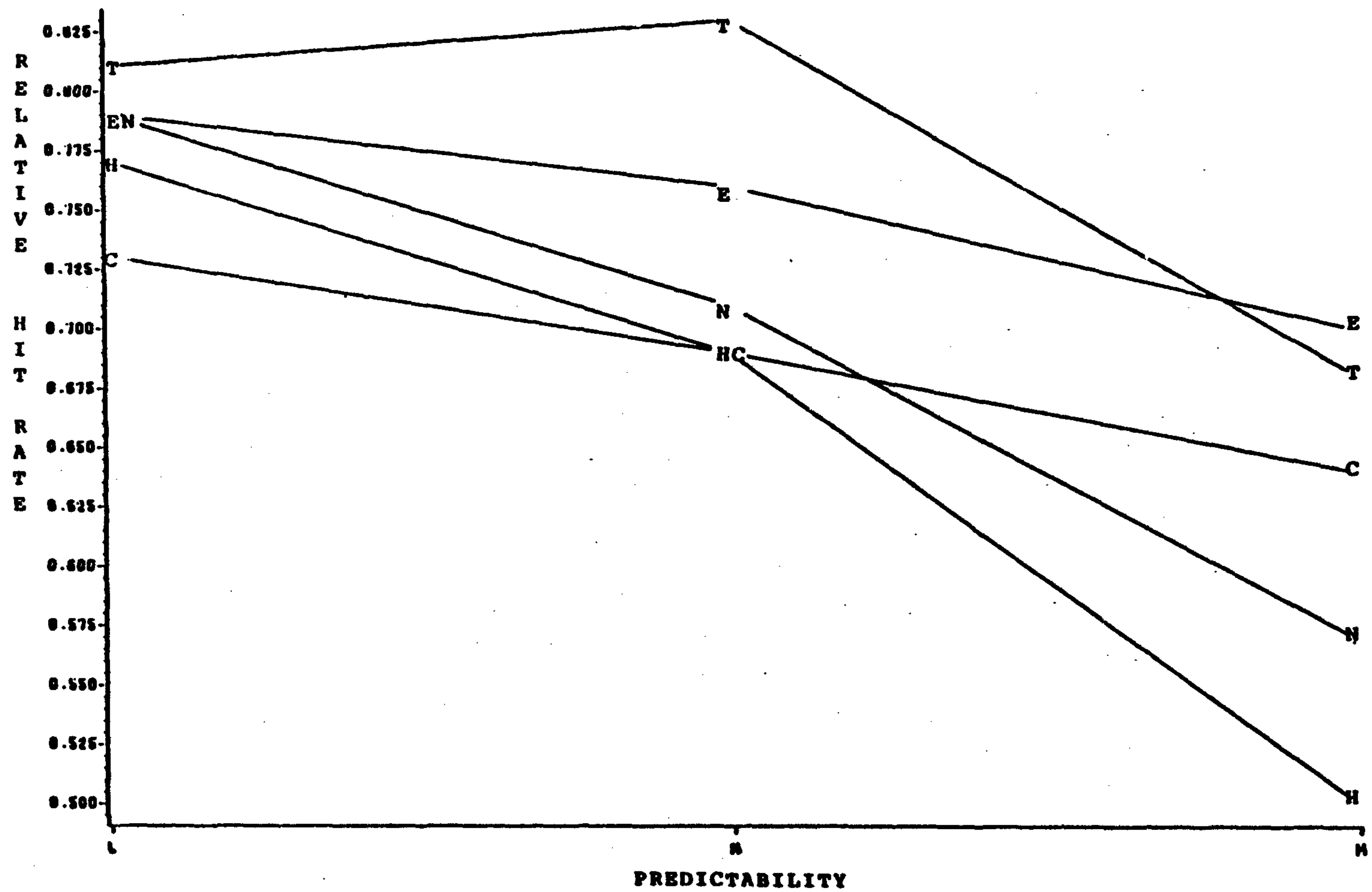



FIGURE 14: RELATIVE HIT RATE BY BLOCKS.

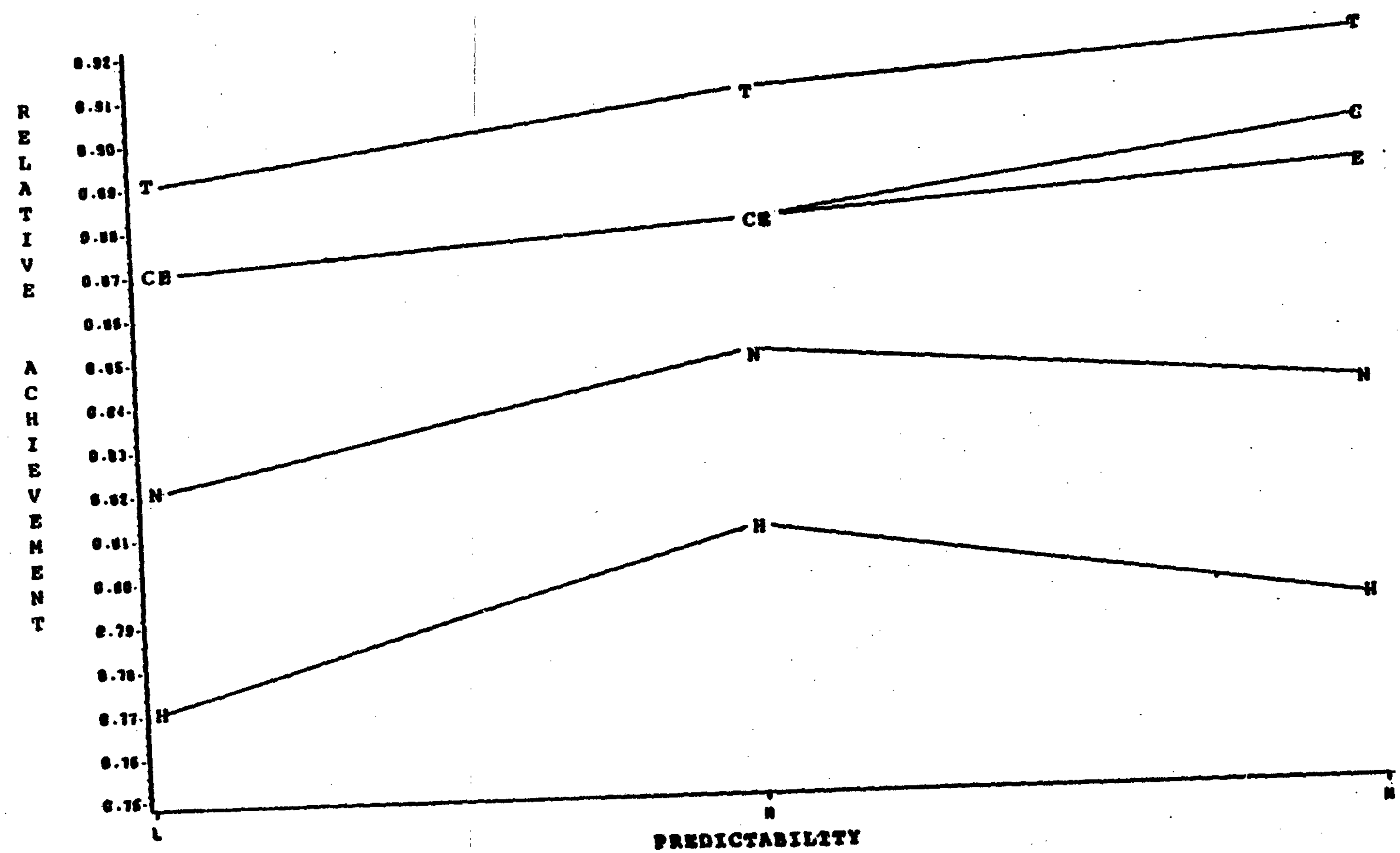



FIGURE 15: RELATIVE ACHIEVEMENT BY BLOCKS.

## Conclusions

The present study shows that feedback efficacy is influenced by task predictability, but not in the way suggested by Adelman's hypothesis. Merely knowing the rule by which predictive information is related to consequent outcomes does not insure that DM will make good use of feedback either for applying that rule more consistently or for maintaining a level of performance. In fact, subjects did show improvement over successive trial blocks (largely as a function of improved consistency), but not because of the contribution of feedback: the no-feedback control subjects did equally as well as the best feedback subjects at all levels of predictability.

What feedback did contribute was all negative, and that negative contribution increased as the task became more predictable. In particular, outcome feedback hurt performance and did so more seriously as task predictability increased, much as if the "noise" (or unpredictable) component were amplified by DM relative to the "signal" component as task conditions improved. Preserving records of past outcomes and responses only served to worsen the situation rather than "dampen out" the fluctuations. On the other hand, response (cognitive) feedback produced no decrement regardless of task predictability. Presumably, whatever cognitive representation of the proper weighting strategy was established at the outset was left undisturbed by both metric and directional feedback. Of course, since neither kind of feedback produced any differential improvement (relative to the control condition), it was clearly not necessary for either the preservation or reinforcment of that cognitive representation.

There remains, then, a discrepancy between the influence of two task properties (congruence and predictability) on the efficacy of feedback in general and outcome feedback in particular. Making DM's task clearer by increasing congruence apparently promotes the usefulness of outcome feedback; doing so by improving the "signal-to-noise" ratio (predictability) only promotes the harmfulness of outcome feedback. Since these generalizations derive from separate studies, the next step toward clarification would seem to lie in the direction of concurrent investigation.

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Arlington, VA 22202

Dr. Howard E. Clark
NAS-NRC
Commission on Engrg. & Tech. Systems
2101 Constitution Ave., N.W.
Washington, D.C. 20418

Other Organizations

Dr. Charles Gettys
Department of Psychology
University of Oklahoma
455 West Lindsey
Norman, OK 73069

Dr. Kenneth Hammond
Institute of Behavioral Science
University of Colorado
Boulder, CO 80309

Dr. James H. Howard, Jr.
Department of Psychology
Catholic University
Washington, D. C. 20064

Dr. William Howell
Department of Psychology
Rice University
Houston, TX 77001

Dr. Christopher Wickens
Department of Psychology
University of Illinois
Urbana, IL 61801

Mr. Edward M. Connelly
Performance Measurement
Associates, Inc.
410 Pine Street, S. E.
Suite 300
Vienna, VA 22180

Professor Michael Athans
Room 35-406
Massachusetts Institute of
Technology
Cambridge, MA 02139

Dr. Edward R. Jones
Chief, Human Factors Engineering
McDonnell-Douglas Astronautics Co.
St. Louis Division
Box 516
St. Louis, MO 63166

Other Organizations

Dr. Babur M. Pulat
Department of Industrial Engineering
North Carolina A&T State University
Greensboro, NC 27411

Dr. Lola Lopes
Information Sciences Division
Department of Psychology
University of Wisconsin
Madison, WI 53706

National Security Agency
ATTN: N-32, Marie Goldberg
9800 Savage Road
Ft. Meade, MD 20722

Dr. Stanley N. Roscoe
New Mexico State University
Box 5095
Las Cruces, NM 88003

Mr. Joseph G. Wohl
Alphatech, Inc.
3 New England Executive Park
Burlington, MA 01803

Dr. Marvin Cohen
Decision Science Consortium, Inc.
Suite 721
7700 Leesburg Pike
Falls Church, VA 22043

Dr. Robert Wherry
Analytics, Inc.
2500 Maryland Road
Willow Grove, PA 19090

Dr. William R. Uttal
Institute for Social Research
University of Michigan
Ann Arbor, MI 48109

Dr. William B. Rouse
School of Industrial and Systems
Engineering
Georgia Institute of Technology
Atlanta, GA 30332

May 1984

Other Organizations

Dr. Richard Pew
Bolt Beranek & Newman, Inc.
50 Moulton Street
Cambridge, MA 02238

Dr. Hillel Einhorn
Graduate School of Business
University of Chicago
1101 E. 58th Street
Chicago, IL 60637

Dr. Douglas Towne
University of Southern California
Behavioral Technology Lab
3716 S. Hope Street
Los Angeles, CA 90007

Dr. David J. Getty
Bolt Beranek & Newman, Inc.
50 Moulton street
Cambridge, MA 02238

Dr. John Payne
Graduate School of Business
Administration
Duke University
Durham, NC 27706

Dr. Baruch Fischhoff
Decision Research
1201 Oak Street
Eugene, OR 97401

Dr. Alan Morse
Intelligent Software Systems Inc.
160 Old Farm Road
Amherst, MA 01002

Dr. J. Miller
Florida Institute of Oceanography
University of South Florida
St. Petersburg, FL 33701